Adult2child: Motion Style Transfer using CycleGANs

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Motivation

- Child characters have gained popularity in the animation and gaming industries.
- Most of the work focused on creating adult motions, but very few for child motions.





Challenges

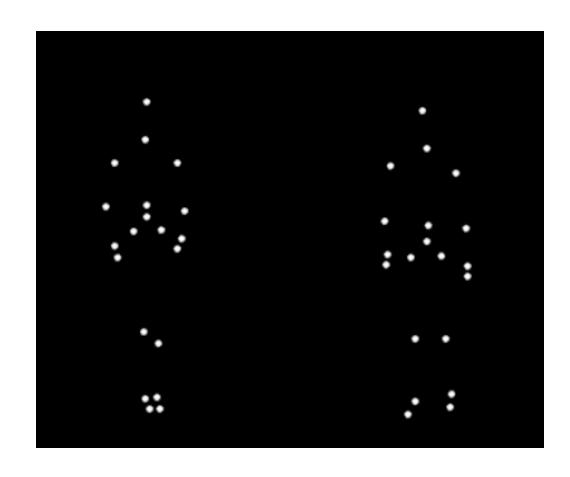
- Difficulties of motion capturing children
 - Lack of patience
 - Easily distracted
 - Hard to follow instructions





Challenges

- Given the difficulties of motion capturing children, can we just use adult mocap data on child characters?
- Can we convince the viewers that the motions are from children?
- Jain et al[2016] found that viewers can differentiate child motion from adult motion by viewing point light display videos.





Key Ideas

- Adapt adult motions to child motions that captures both the postures and the timing of child motions.
- Achieve this goal without temporally aligned data given that adult motions and child motions can be drastically different.



Contributions

• Architecture:

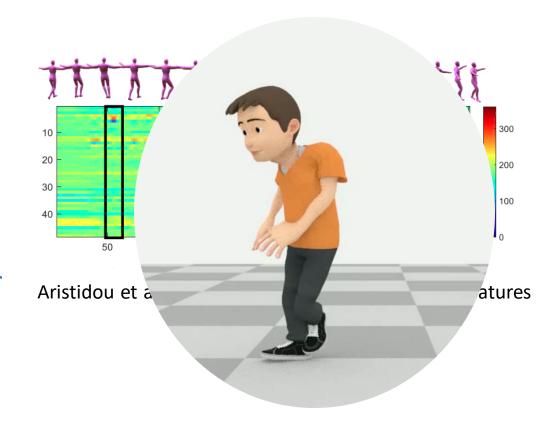
- First to adapt cycleGAN for motion style transfer that can alter timing.
- Redesigned the generators and the discriminators. No temporal alignment.
- Additional loss terms to output natural and smooth motions.

Representation:

- Espouse joint angles as an animationcentric representation. Facilitate character binding and skinning.
- Motion words to encode temporal/spatial information.

Dataset:

Released a high-quality optical mocap dataset of children.





Related work

Zhu et al.[2017]^[1]

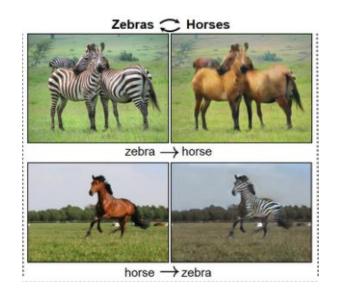
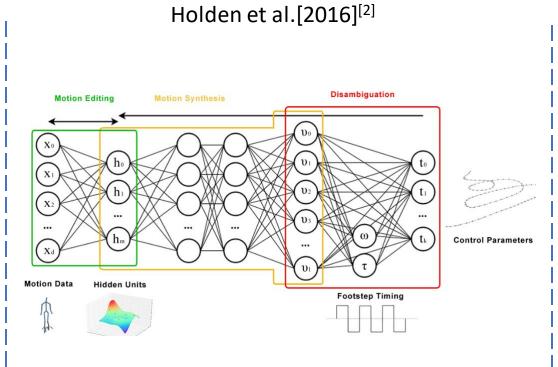


Image style transfer with unpaired training data



Learn motion manifold from a large dataset(six millions frames)

Aberman et al.[2020]^[3]

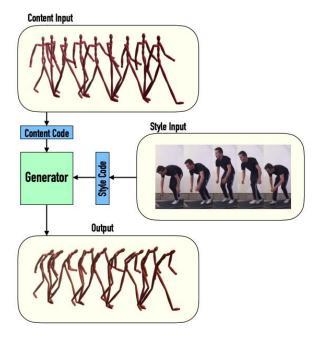


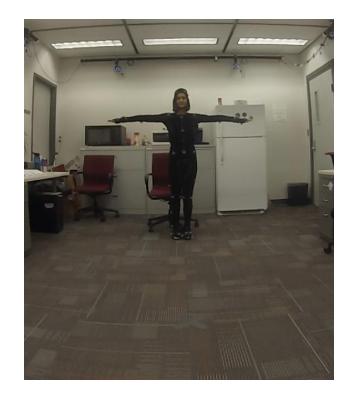
Image style transfer with unpaired training data

- [1] Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." *Proceedings of the IEEE international conference on computer vision*. 2017.
- [2] Holden, Daniel, Jun Saito, and Taku Komura. "A deep learning framework for character motion synthesis and editing." ACM Transactions on Graphics (TOG) 35.4 (2016): 1-11.
- [3] Aberman, K., Weng, Y., Lischinski, D., Cohen-Or, D., & Chen, B. (2020). Unpaired Motion Style Transfer from Video to Animation. arXiv preprint arXiv:2005.05751.



Our Novel Child Dataset: Kinder-Gator 2.0

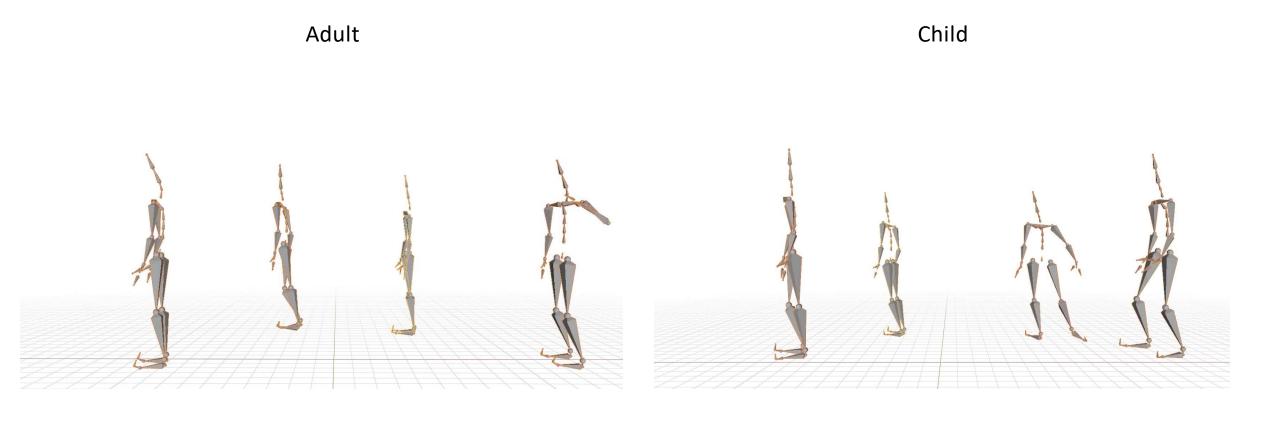
- 8 children (5-10 years old). 9 adults: (18 years old and above).
- ``Jumping jacks", ``Throw a ball", ``Walk", ``Walk as fast as you can", ``Hop scotch", ``Punch", ``Kick", ``Jog", ``Run as fast as you can", etc.
- 2-3 repetitions for each action type.





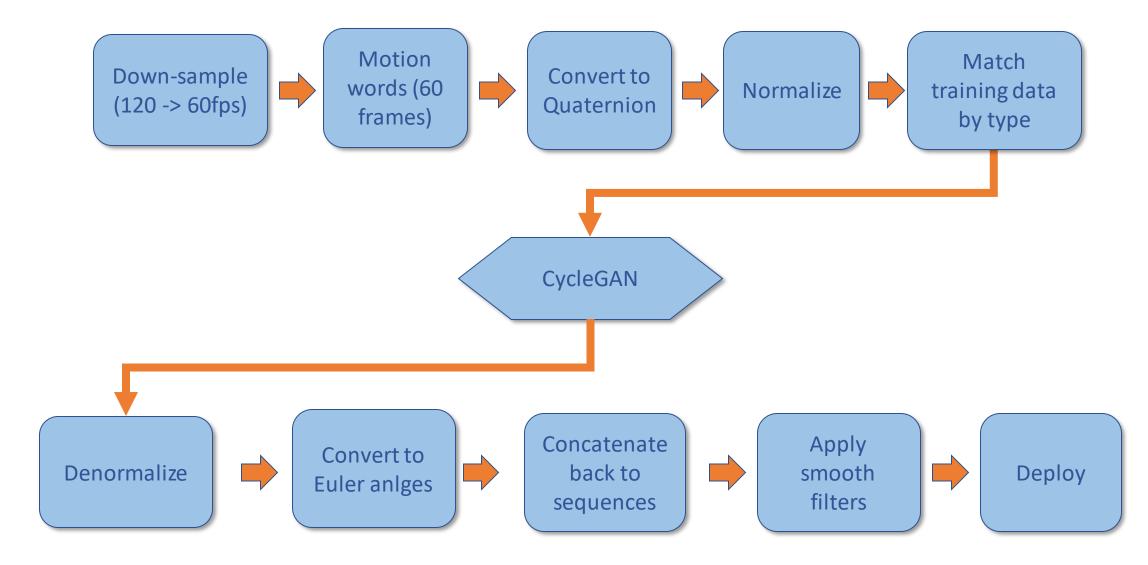


Examples from Kinder-Gator 2.0





Pipeline





Overall Architecture

Adversarialloss $\mathcal{L}_{G_{c2a}} = 0.5 * \mathbb{E}_{c \sim p(c)} [D_a(G_{c2a}(c)) - 1]$

$$\mathcal{L}_{G_{a2c}} = 0.5 * \mathbb{E}_{a \sim p(a)}[D_c(G_{a2c}(a)) - 1]$$

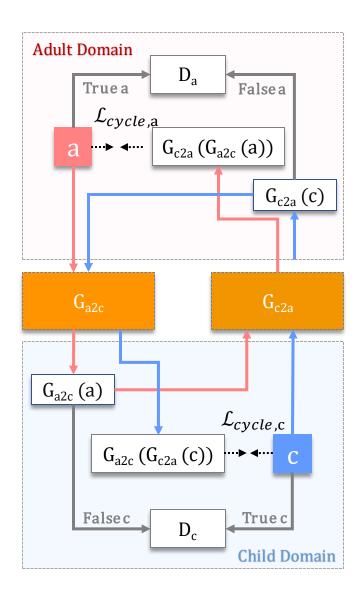
Cycle loss $\mathcal{L}_{cycle,c} = G_{a2c}(G_{c2a}(c)) - c$

$$\mathcal{L}_{cycle,a} = G_{c2a}(G_{a2c}(a)) - a$$

Coherence loss $\mathcal{L}_{coherence, \mathbf{a}} = \sum_{t} \sum_{DOF} ||\mathbf{G}_{\mathbf{a2c}}(\mathbf{a})(t) - \mathbf{G}_{\mathbf{a2c}}(\mathbf{a})(t-1)||$

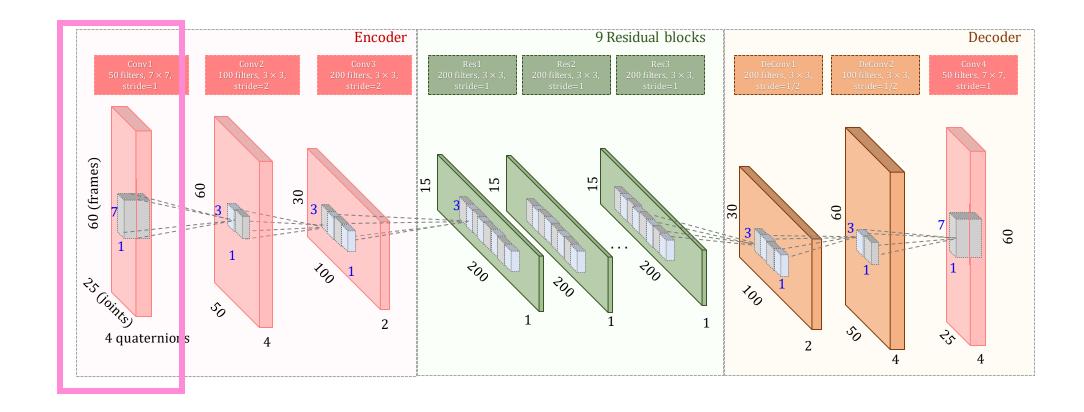
$$\mathcal{L}_{coherence, \mathbf{c}} = \sum_{t} \sum_{DOF} ||\mathbf{G}_{\mathbf{c}2\mathbf{a}}(\mathbf{c})(t) - \mathbf{G}_{\mathbf{c}2\mathbf{a}}(\mathbf{c})(t-1)||$$

Transition loss $y = G_{c2a}(c)$ $\mathcal{L}_{transition,c} = \sum_{t} \sum_{P \in F} ||y_i(t_{overlap:end}) - y_{i+1}(0:t_{overlap})||$





Generator's Architecture

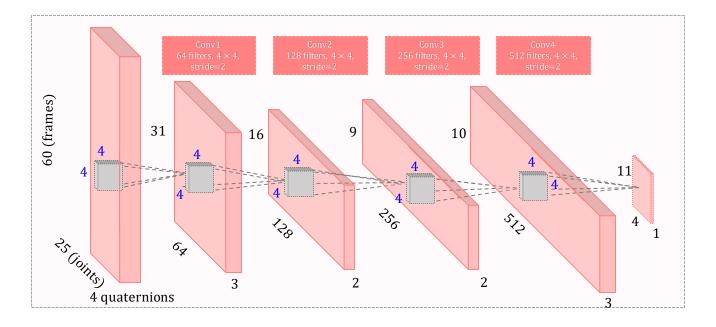


Convolution convolves along the quaternion axis and the temporal axis



Discriminator's Architecture

Patch GANs





Implementation Details

- We implemented and trained the model on Google Colab Pro with P100 or T4 graphics card.
- The model was written in Python using TensorFlow library.
- We trained the model for 180 epochs and the training takes ~7 hours.
- The trained model is 8.67MB.





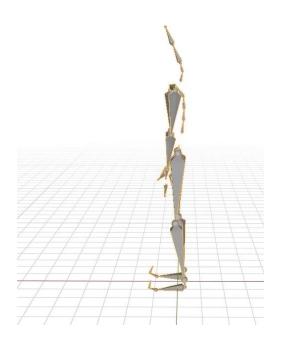


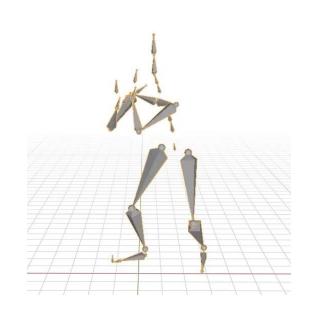
Our Results: Punch

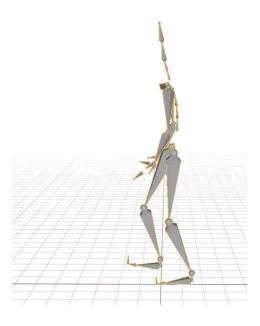
Input adult

Ours

Reference child



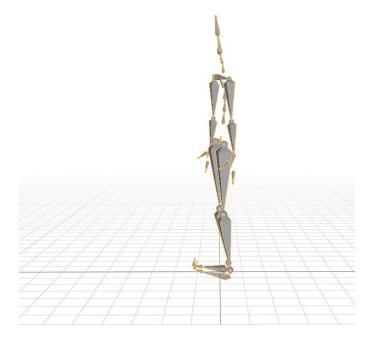


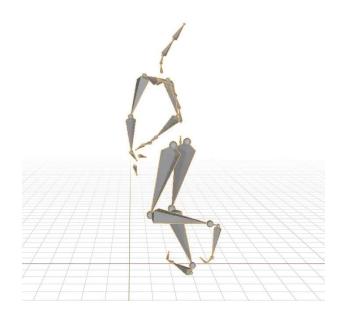




Our Results: Run as fast as you can

Input adult Ours Reference child

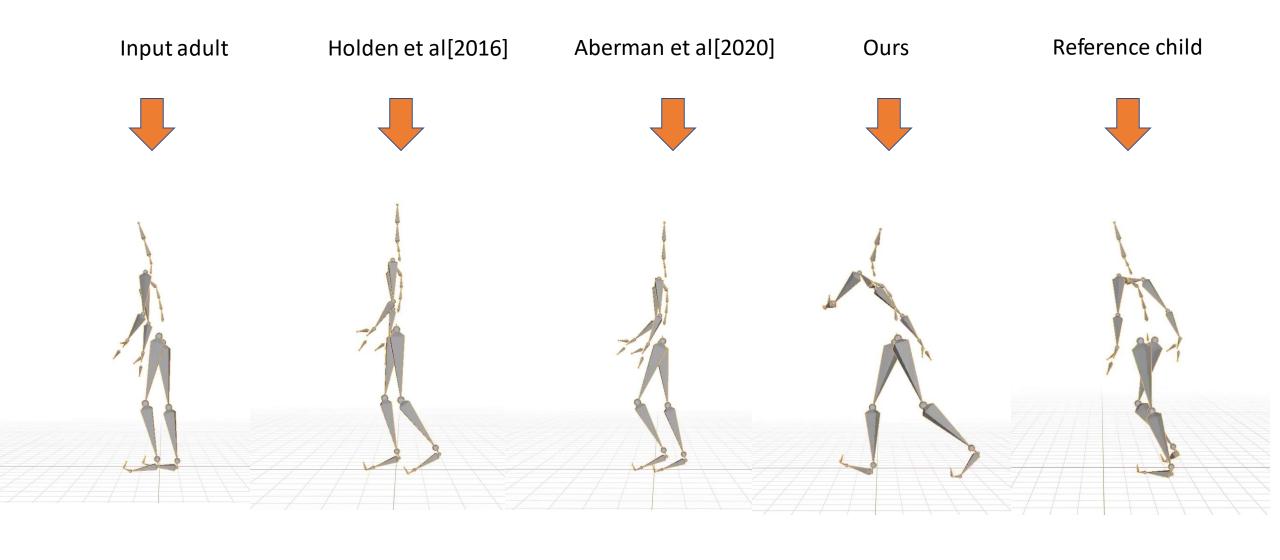






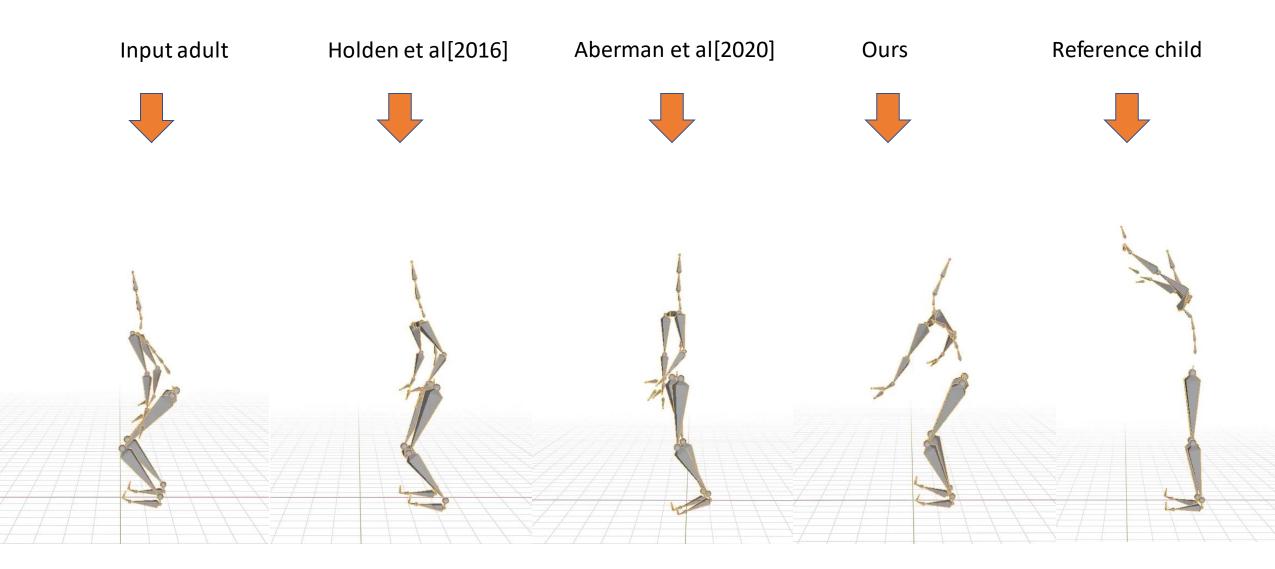


Compare with state-of-the-art: Walk as fast as you can





Compare with state-of-the-art: Jump as high as you can





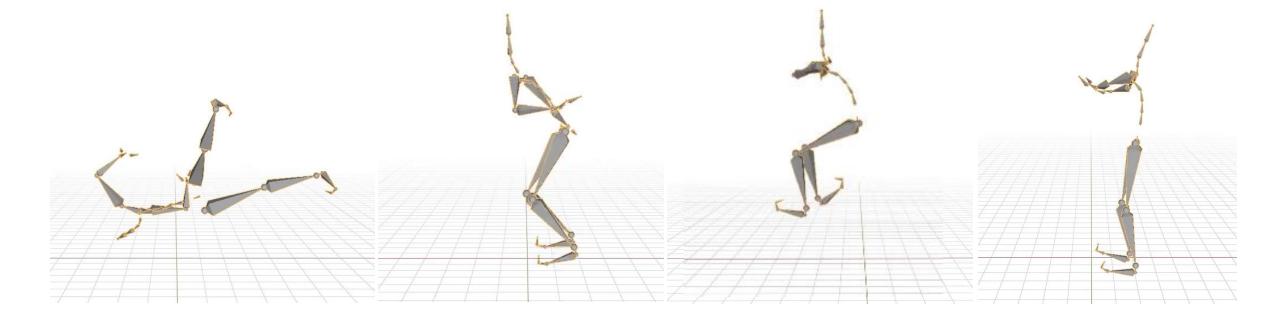
Ablation Studies

Overall loss

No cycle loss

No coherence loss

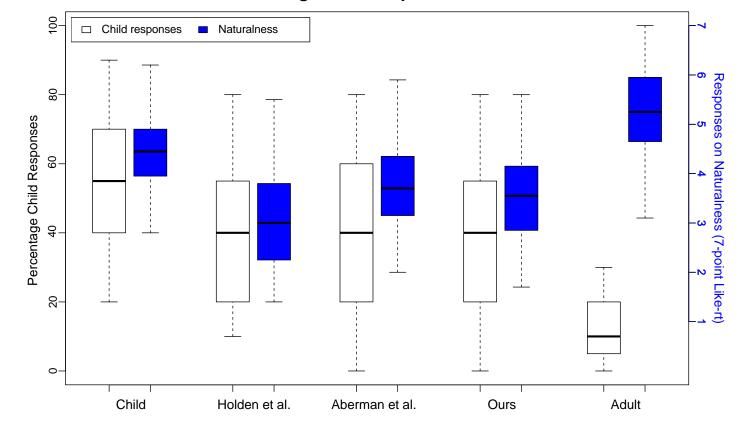
With transition loss advesarial+cycle+coherence



Perceptual Study

- Point light display of five conditions: child, adult, Aberman, Holden, ours
- 41 participants
- Does this motion belong to a Child or an Adult? (Child/Adult)
- Indicate the naturalness of the motion on a 7-point Likert scale.





Conclusion

- We have presented a method that allows adult2child style transfer,
- We have introduced two additional losses to condition the network, temporal coherency loss, and transition loss.
- The use of motion words helps the network to learn both the spatial and temporal information about motions.



Future Work

- Remove foot sliding/skating by adding constraints (inverse kinematics).
- Investigate mechanisms to change the sequence length and allow smooth blending.
- CycleGAN introduce noise in the output (unexpected angle). Explore additional constraints to reduce jitters.

Code download (in preparation):

https://gitlab.com/jainlab/cyclegan-1-

master

Dataset download:

https://jainlab.cise.ufl.edu/publication s.html#Adult2ChildCycleGAN



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